1	A robust phylogenomic timetree for biotechnologically and
2	medically important fungi from Aspergillaceae (Eurotiomycetes,
3	Ascomycota)
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19	Abbreviations: NT, nucleotide; AA, amino acid; CI, confidence interval; RCV, relative
20	composition variability; IC, internode certainty; GSF, gene support frequencies; GLS, gene-wise
21	log-likelihood scores; DVMC, degree of violation of a molecular clock;

22 Abstract

23 The filamentous fungal family Aspergillaceae contains > 1,000 known species, mostly in the 24 genera Aspergillus and Penicillium. Fungi in Aspergillaceae display a wide range of lifestyles, 25 including several that are of relevance to human affairs. For example, several species are used as 26 industrial workhorses, food fermenters, or platforms for drug discovery (e.g., Aspergillus niger, 27 Penicillium camemberti), while others are dangerous human and plant pathogens (e.g., 28 Aspergillus fumigatus, Penicillium digitatum). Reconstructing the phylogeny and timeline of the 29 family's diversification is the first step toward understanding how its diverse range of lifestyles 30 evolved. To infer a robust phylogeny for Aspergillaceae and pinpoint poorly resolved branches 31 and their likely underlying contributors, we used 81 genomes spanning the diversity of 32 Aspergillus and Penicillium to construct a 1,668-gene data matrix. Phylogenies of the nucleotide 33 and amino acid versions of this full data matrix were generated using three different maximum 34 likelihood schemes (i.e., gene-partitioned, unpartitioned, and coalescence). We also used the 35 same three schemes to infer phylogenies from five additional 834-gene data matrices constructed by subsampling the top 50% of genes according to different criteria associated with strong 36 37 phylogenetic signal (alignment length, average bootstrap value, taxon completeness, treeness / 38 relative composition variability, and number of variable sites). Examination of the topological 39 agreement among these 36 phylogenies and measures of internode certainty identified 12 / 7840 (15.4%) bipartitions that were incongruent. Patterns of incongruence across these 12 bipartitions 41 fell into three categories: (i) low levels of incongruence for 2 shallow bipartitions, most likely 42 stemming from incomplete lineage sorting, (ii) high levels of incongruence for 3 shallow 43 bipartitions, most likely stemming from hybridization or introgression (or very high levels of 44 incomplete lineage sorting), and (iii) varying levels of incongruence for 7 deeper bipartitions,

45 most likely stemming from reconstruction artifacts associated with poor taxon sampling. Relaxed

- 46 molecular clock analyses suggest that Aspergillaceae likely originated in the lower Cretaceous,
- 47 125.1 (95% Confidence Interval (CI): 146.7 102.1) million years ago (mya), with the origins of
- 48 the Aspergillus and Penicillium genera dating back to 84.3 mya (95% CI: 90.9 77.6) and 77.4
- 49 mya (95% CI: 94.0 61.0), respectively. Our results provide a robust evolutionary and temporal
- 50 framework for comparative genomic analyses in Aspergillaceae, while our general approach
- 51 provides a widely applicable template for phylogenomic identification of resolved and
- 52 contentious branches in densely genome-sequenced lineages across the tree of life.

53 The vast majority of the 1,062 described species from the family Aspergillaceae (phylum 54 Ascomycota, class Eurotiomycetes, order Eurotiales)¹ belong to the genera Aspergillus (42.5%; 451 / 1.062) and *Penicillium* (51.6%; 549 / 1.062)^{2,3}. Fungi from Aspergillaceae exhibit diverse 55 56 ecologies; for example, Penicillium verrucosum is widespread in cold climates but has yet to be 57 isolated in the tropics⁴, whereas Aspergillus nidulans is able to grow at a wide range of temperatures but favors warmer temperatures⁵. Several representative species in the family are 58 59 exploited by humans, while a number of others are harmful to humans or their activities⁶. For 60 example, Aspergillus oryzae is used in the production of traditional Japanese foods including soy sauce, sake, and vinegar^{7,8}, Penicillium camemberti and Penicillium roqueforti contribute to 61 62 cheese production^{9,10}, Aspergillus niger is used in the production of enzymes that are later used 63 in starch processing, baking and brewing industries, in animal feed, and the paper industry¹¹, and 64 Penicillium citrinum produces the cholesterol lowering drug mevastatin, the world's first statin 65 (Endo 2010). In contrast, Aspergillus fumigatus and Aspergillus flavus are pathogens, allergens, and mycotoxin producers^{13,14} and *Penicillium expansum*, *Penicillium digitatum*, and *Penicillium* 66 67 *italicum* are post-harvest pathogens of citrus fruits, stored grains, and other cereal crops^{15–17}.

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Much of the rich diversity of ecologies and wide impact on human affairs that Aspergillaceae exhibit has been attributed to the remarkable chemical diversity of secondary metabolites, small molecules that function as toxins, signaling molecules, and pigments, that organisms in this family produce^{18–20}. For example, diminished global production of secondary metabolites in *A*. *nidulans* caused by knocking-out the master regulator of secondary metabolism, *laeA*, resulted in increased predation by the collembolan fungivore, *Folsomia candida*, which suggests that these compounds play defensive roles²¹. Other studies investigating single secondary metabolites have

76 shown that these small molecules often have biological activities that are either harmful or 77 beneficial to human welfare. For example, the A. fumigatus-produced secondary metabolite gliotoxin is a potent virulence factor in cases of systemic mycosis in vertebrates²², and the A. 78 79 flavus-produced secondary metabolite aflatoxin is among the most toxic and carcinogenic naturally occurring compounds^{19,23}. In contrast, other secondary metabolites are mainstay 80 81 antibiotics and pharmaceuticals; for example, the *Penicillium chrysogenum*-produced penicillin 82 is among the world's most widely used antibiotics²⁴⁻²⁶ and the *P. citrinum*-produced cholesterol 83 lowering statins are consistently among the world's blockbuster drugs¹². 84 85 Understanding the evolution of the diverse ecological lifestyles exhibited by Aspergillaceae 86 members as well as the family's remarkable chemodiversity requires a robust phylogenetic 87 framework. To date, most molecular phylogenies of the family Aspergillaceae are derived from 88 single or few genes and have yielded conflicting results. For example, there is little consensus on 89 whether the genus Aspergillus is monophyletic or if it includes species from other genera such as 90 *Penicillium*^{27,28}. Furthermore, studies using genome-scale amounts of data, which could have the 91 power to resolve evolutionary relationships and identify underlying causes of conflict^{29,30}, have so far tended to use a small subset of fungi from either Aspergillus or Penicillium^{31–33}. 92 93 Additionally, these genome-scale studies typically build one phylogeny and, based on the high 94 clade support values (e.g., bootstrap values) obtained, infer or assume that the topology obtained 95 is highly accurate $^{31-34}$.

96

In very recent years, several phylogenomic analyses have shown that incongruence, the presence
of topological conflict between different data sets or analyses, is widespread^{29,35–37}, and that

99 certain branches of the tree of life can be very challenging to resolve, even with genome-scale amounts of data³⁸⁻⁴². For example, analyses of the currently available genome-scale amounts of 100 101 data have not resolved the placement of the budding yeast family Ascoideaceae in the fungal 102 subphylum Saccharomycotina (phylum: Ascomycota)^{38,42,43}. Comparison of the topologies inferred in previous phylogenomic studies in Aspergillaceae³¹⁻³⁴ suggests the presence of 103 104 incongruence (Figure S1). For example, some studies have reported section *Nidulantes* to be the 105 sister group to section Nigri³¹, whereas other studies have placed it as the sister group to Ochraceorosei³³ (Figure S1). 106

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108 To systematically evaluate the evolutionary relationships among Aspergillaceae and identify 109 instances of incongruence, we used the genome sequences of 81 fungi from Aspergillaceae 110 spanning 4 genera, 24 sections within Aspergillus and Penicillium, and 12 outgroup fungi to 111 construct nucleotide (NT) and amino acid (AA) versions of a 1,668-gene data matrix. Using 112 three different maximum likelihood schemes (i.e., gene-partitioned, unpartitioned, and 113 coalescence), we inferred phylogenies from the 1,668-gene data matrix as well as from five 114 additional 834-gene data matrices derived from the top 50% of genes harboring strong 115 phylogenetic signal according to five different criteria (alignment length, average bootstrap 116 value, taxon completeness, treeness / relative composition variability, and number of variable 117 sites). Comparisons of these phylogenies coupled with complementary measures of internode 118 certainty^{29,44,45} identified 12 / 78 (15.4%) incongruent bipartitions in the phylogeny of 119 Aspergillaceae. These cases of incongruence can be grouped into three categories: (i) 2 shallow 120 bipartitions with low levels of incongruence likely driven by incomplete lineage sorting, (ii) 3 121 shallow bipartitions with high levels of incongruence likely driven by hybridization or

- 122 introgression (or very high levels of incomplete lineage sorting), and (iii) 7 deeper bipartitions
- 123 with varying levels of incongruence likely driven by reconstruction artifacts likely linked with
- 124 poor taxon sampling. We also estimated divergence times across Aspergillaceae using relaxed
- 125 molecular clock analyses. Our results suggest Aspergillaceae originated in the lower Cretaceous,
- 126 125.1 (95% Confidence Interval (CI): 146.7 102.1) million years ago (mya), and that
- 127 Aspergillus and Penicillium originated 84.3 mya (95% CI: 90.9 77.6) and 77.4 mya (95% CI:
- 128 94.0 61.0), respectively. We believe this phylogeny and timetree provides a state-of-the-art
- 129 platform for comparative genomic, ecological, and chemodiversity studies in this ecologically
- 130 diverse and biotechnologically and medically significant family of filamentous fungi.

131 Methods

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133 Genome sequencing and assembly

134 Mycelia were grown on potato dextrose agar for 72 hours before lyophilization. Lyophilized

135 mycelia were lysed by grinding in liquid nitrogen and suspension in extraction buffer (100 mM

136 Tris-HCl pH 8, 250 mM NaCl, 50 mM EDTA, and 1% SDS). Genomic DNA was isolated from

137 the lysate with a phenol/chloroform extraction followed by an ethanol precipitation.

138

139 DNA was sequenced with both paired-end and mate-pair strategies to generate a high-quality

140 genome assembly. Paired-end libraries and Mate-pair libraries were constructed at the Genomics

141 Services Lab at HudsonAlpha (Huntsville, Alabama) and sequenced on an Illumina HiSeq X

sequencer. Paired-end libraries were constructed with the Illumina TruSeq DNA kit, and mate-

143 pair libraries were constructed with the Illumina Nextera Mate Pair Library kit targeting an insert

size of 4 Kb. In total, 63 million paired-end reads and 105 million mate-pair reads were

145 generated.

146

The *A. delacroxii* genome was assembled using the iWGS pipeline⁴⁶. Paired-end and mate-pair
reads were assembled with SPADES, version 3.6.2⁴⁷, using optimal k-mer lengths chosen using
KMERGENIE, version 1.6982⁴⁸ and evaluated with QUAST, version 3.2⁴⁹. The resulting assembly
is 33.8 MB in size with an N50 of 939 Kb.

151

152 **Data collection and quality assessment**

153 To collect a comprehensive set of genomes representative of Aspergillaceae, we used 154 'Aspergillaceae' as a search term in NCBI's Taxonomy Browser and downloaded a 155 representative genome from every species that had a sequenced genome as of February 5th 2018. 156 We next confirmed that each species belonged to Aspergillaceae according to previous literature reports^{31,50}. Altogether, 80 publicly available genomes and 1 newly sequenced genome spanning 157 158 5 genera (45 Aspergillus species; 33 Penicillium species; one Xeromyces species; one Monascus 159 species; and one *Penicilliopsis* species) from the family Aspergillaceae were collected (File S1). 160 We also retrieved an additional 12 fungal genomes from representative species in the order 161 Eurotiales but outside the family Aspergillaceae to use as outgroups. 162 163 To determine if the genomes contained gene sets of sufficient quality for use in phylogenomic 164 analyses, we examined their gene set completeness using Benchmarking Universal Single-Copy 165 Orthologs (BUSCO), version 2.0.1⁵¹ (Figure S2). In brief, BUSCO uses a consensus sequence 166 built from hidden Markov models derived from 50 different fungal species using HMMER, version 3.1b2⁵² as a query in TBLASTN^{53,54} to search an individual genome for 3,156 predefined 167 168 orthologs (referred to as BUSCO genes) from the Pezizomycotina database (creation date: 02-13-169 2016) available from ORTHODB, version 9⁵⁵. To determine the copy number and completeness 170 of each BUSCO gene in a genome, gene structure is predicted using AUGUSTUS, version

171 2.5.5⁵⁶, from the nucleotide coordinates of putative genes identified using BLAST and then

172 aligned to the HMM alignment of the same BUSCO gene. Genes are considered "single copy" if

173 there is only one complete predicted gene present in the genome, "duplicated" if there are two or

174 more complete predicted genes for one BUSCO gene, "fragmented" if the predicted gene is

- shorter than 95% of the aligned sequence lengths from the 50 different fungal species, and
 "missing" if there is no predicted gene.
- 177

178 **Phylogenomic data matrix construction**

179 In addition to their utility as a measure of genome completeness, BUSCO genes have also proven to be useful markers for phylogenomic inference⁵⁷, and have been successfully used in 180 181 phylogenomic studies of clades spanning the tree of life, such as birds⁵⁸, insects⁵⁹, and budding 182 yeasts³⁸. To infer evolutionary relationships, we constructed nucleotide (NT) and amino acid 183 (AA) versions of a data matrix comprised of the aligned and trimmed sequences of numerous 184 BUSCO genes (Figure S3). To construct this data matrix, we first used the BUSCO output 185 summary files to identify orthologous single copy BUSCO genes with > 50% taxon-occupancy 186 (i.e., greater than 47 / 93 taxa have the BUSCO gene present in their genome); 3,138 (99.4%) 187 BUSCO genes met this criterion. For each BUSCO gene, we next created individual AA fasta 188 files by combining sequences across all taxa that have the BUSCO gene present. For each gene 189 individually, we aligned the sequences in the AA fasta file using MAFFT, version $7.294b^{60}$, with the BLOSUM62 matrix of substitutions⁶¹, a gap penalty of 1.0, 1,000 maximum iterations, and 190 191 the 'genafpair' parameter. To create a codon-based alignment, we used a custom PYTHON, 192 version 3.5.2 (https://www.python.org/), script using BIOPYTHON, version 1.7⁶², to thread codons 193 onto the AA alignment. The NT and AA sequences were then individually trimmed using 194 TRIMAL, version 1.4⁶³, with the 'automated1' parameter. We next removed BUSCO genes 195 whose sequence lengths were less than 50% of the untrimmed length in either the NT or AA 196 sequences resulting in 1,773 (56.2%) BUSCO genes. Lastly, we removed BUSCO genes whose 197 trimmed sequence lengths were too short (defined as genes whose alignment length was less than

or equal to 167 AAs and 501 NTs), resulting in 1,668 (52.9%) BUSCO genes. The NT and AA
alignments of these 1,668 BUSCO genes were then concatenated into the full 1,668-gene NT and
AA versions of the phylogenomic data matrix.

201

202 To examine the stability of inferred relationships across all taxa, we constructed additional NT 203 and AA data matrices by subsampling genes from the 1,668-gene data matrix that harbor 204 signatures of strong phylogenetic signal. More specifically, we used 5 measures associated with strong phylogenetic signal⁶⁴ to create 5 additional data matrices (1 data matrix per measure) 205 206 comprised of the top scoring 834 (50%) genes for NTs and AAs (Figure S4). These five 207 measures were: alignment length, average bootstrap value, taxon completeness, treeness / relative composition variability (RCV)⁶⁵, and the number of variable sites. We calculated each 208 209 measure with custom PYTHON scripts using BIOPYTHON. Treeness / RCV was calculated using 210 the following formula:

211
$$\frac{Treeness}{RCV} = \frac{\sum_{u=1}^{b} l_u / l_t}{\sum_{i=1}^{c} \sum_{j=1}^{n} \frac{|c_{ij} - \overline{c_i}|}{s \cdot n}}$$

where l_u refers to the internal branch length of the *u*th branch (of *b* internal branches), l_t refers to total tree length, *c* is the number of different characters per sequence type (4 for nucleotides and 20 for amino acids), *n* is the number of taxa in the alignment, c_{ij} refers to the number of *i*th *c* characters for the *j*th taxon, $\overline{c_t}$ refers to the average number of the *i*th *c* character across *n* taxa, and *s* refers to the total number of sites in the alignment. Altogether, we constructed a total of 12 data matrices (one 1,668-gene NT data matrix, one 1,668-gene AA data matrix, five NT subsample data matrices, and five AA subsample data matrices).

220 Maximum likelihood phylogenetic analyses

221 We implemented a maximum likelihood framework to infer evolutionary relationships among 222 taxa for each of the 1,668 single genes and each of the 12 data matrices separately. For 223 inferences made using either the 1,668- or 834-gene data matrices, we used three different 224 analytical schemes: concatenation with gene-based partitioning, concatenation without partitioning, and gene-based coalescence^{30,66–68}. All phylogenetic trees were built using IQ-225 226 TREE, version $1.6.1^{69}$. In each case, we first determined the best model for each single gene or 227 partition using the "-m TEST" parameter, which automatically estimates the best fitting model of 228 substitutions according to their Bayesian Information Criterion values for either NTs or AAs⁷⁰. Because we were unsure if downstream analyses may include the use of RAXML⁷¹, we restricted 229 the models tested and used to those shared by RAXML⁷¹ and IQ-TREE by using the "-mset" 230

231 parameter.

232

233 We first examined the inferred best fitting models across all single gene trees. Among NT genes, 234 the best fitting model for 1,643 genes was a general time reversible model with unequal rates and unequal base frequencies with discrete gamma models, "GTR+G4"⁷²⁻⁷⁴, and for the remaining 25 235 236 genes was a general time reversible model with invariable sites plus discrete gamma models, 237 "GTR+I+G4"^{74,75} (Figure S5a). Among AA genes, the best fitting model for 643 genes was the 238 JTT model with invariable sites plus discrete gamma models, "JTT+I+G4"^{75,76}, for 362 genes 239 was the LG model with invariable sites and discrete gamma models, "LG+I+G4"^{75,77}, for 225 240 genes was the JTT model with invariable sites, empirical AA frequencies, and discrete gamma models "JTT+F+I+G4"^{75,76}, and for 153 genes was the JTTDCMut model with invariable sites 241 and discrete gamma models, "JTTDCMut+I+G4"^{75,78} (Figure S5b). 242

243

We used IQ-TREE for downstream analysis because a recent study using diverse empirical
phylogenomic data matrices showed that it is a top-performing software⁷⁹ as well as because IQTREE's gene partitioning scheme can account for different models of rate heterogeneity per
gene⁸⁰.

248

249 To determine the phylogeny of Aspergillaceae using a partitioned scheme where each gene has 250 its own model of sequence substitution and rate heterogeneity parameters, we created an 251 additional input file describing these and gene boundary parameters. More specifically, we 252 created a nexus-style partition file that was used as input with the "-spp" parameter⁸⁰. To 253 increase the number of candidate trees used during maximum likelihood search, we set the "-254 nbest" parameter to 10. Lastly, we conducted 5 independent searches for the maximum 255 likelihood topology using 5 distinct seeds specified with the "-seed" parameter and chose the 256 search with the best log-likelihood score. We used the phylogeny inferred using a partitioned 257 scheme on the full NT data matrix as the reference one for all subsequent comparisons (Figure 258 1).

259

To determine the phylogeny of Aspergillaceae using a non-partitioned scheme, we used all the same parameters as above; the only difference was that we used a single model of sequence substitution and rate heterogeneity parameters across the entire matrix. The most appropriate single model was determined by counting which best fitting model was most commonly observed across single gene trees. The most commonly observed model was "GTR+F+I+G4"^{75,81}, which was favored in 1,643 / 1,668 (98.5%) of single genes, and

"JTT+I+G4"^{75,76}, which was favored in 643 / 1,668 (38.5%) of single genes, for NTs and AAs,
respectively, (Figure S5). In each analysis, the chosen model was specified using the "-m"
parameter.

269

To determine the phylogeny of Aspergillaceae using coalescence, a method that estimates
 species phylogeny from single gene trees under the multi-species coalescent⁶⁷, we combined all
 NEWICK^{82,83} formatted single gene trees inferred using their best fitting models into a single file.

273 The resulting file was used as input to ASTRAL-II, version 4.10.12⁶⁸ with default parameters.

274

275 To evaluate support for single gene trees and for the reference phylogeny (Figure 1), we used an ultrafast bootstrap approximation approach (UFBoot)⁸⁴. UFBoot first generates bootstrap 276 277 alignments and creates an initial set of trees to use as a null distribution of starting trees. UFBoot then uses quartet puzzling and the NNI algorithm^{85,86} to sample the local maxima and their 278 279 neighborhoods in tree space while reducing run-time by re-estimating log-likelihood threshold 280 values to ensure only trees with sufficiently high log-likelihood values are investigated. If a new 281 tree exceeds the log-likelihood minimum, which is adaptively estimated based on the number of 282 trees encountered and the number of iterations performed by the quartet puzzling and NNI 283 algorithm, a resampling estimated log-likelihood score^{87,88} is determined for the new tree. If the 284 resampling estimated log-likelihood score is better than the previous tree, the previous tree is 285 replaced with the new tree for the particular bootstrap alignment. Ultimately, this methodology is 3.1-10.2 times faster than rapid bootstrap support⁸⁹, is robust to moderate model violations, and, 286 287 most importantly, generates results that are unbiased compared to classic bootstrapping 288 techniques^{84,90}. Thus, this method allows for a fast and accurate alternative to the classic

bootstrapping approach. To implement UFBoot for the NT 1,668-gene data matrix and single
gene trees, we used the "-bb" option in IQ-TREE with 5,000 and 2,000 ultrafast bootstrap
replicates, respectively.

292

293 Evaluating topological support

294 To identify and quantify incongruence, we used two approaches. In the first approach, we 295 compared the 36 topologies inferred from the full 1,668-gene NT and AA data matrices and five 296 additional 834-gene data matrices (constructed by selecting the genes that have the highest 297 scores in five measures previously shown to be associated with strong phylogenetic signal; see 298 above) using three different maximum likelihood schemes (i.e., gene partitioned, non-299 partitioned, coalescence) and identified all incongruent bipartitions between the reference 300 phylogeny (Figure 1) and the other 35. In the second approach, we scrutinized each bipartition in 301 the reference phylogeny using measures of internode certainty (IC) measures for complete and 302 partial single gene trees^{29,44,45}. To better understand single gene support among conflicting bipartitions, we calculated gene-wise log-likelihood scores (GLS)⁴² and gene support frequencies 303 304 (GSF) for the reference and alternative topologies at conflicting bipartitions. 305

306 Identifying internodes with conflict across subsampled data matrices

307 To identify incongruent bipartitions between the reference phylogeny and the other 35

308 phylogenies, we first included the 36 generated phylogenetic trees into a single file. We next

- 309 evaluated the support of all bipartitions in the reference topology among the other 35
- 310 phylogenies using the "-z" option in RAXML. Any bipartition in the reference phylogeny that
- 311 was not present in the rest was considered incongruent; each conflicting bipartition was

identified through manual examination of the conflicting phylogenies. To determine if sequence
type, subsampling method, or maximum likelihood scheme was contributing to differences in
observed topologies among conflicting internodes, we conducted multiple correspondence
analysis of these features among the 36 phylogenies and visualized results using the R, version
3.3.2⁹¹, packages FACTOMINER, version 1.40⁹² and FACTOEXTRA, version 1.0.5⁹³.

317

318 Identifying internodes with conflict across the 1,668 gene trees

319 To examine the presence and degree of support for bipartitions that conflict with the bipartitions in a given phylogeny, we calculated the internode certainty^{29,44,45,94} of all internodes in the 320 321 reference phylogeny (Figure 1) using the 1,668 gene trees as input. In general, IC scores near 0 322 indicate that there is near-equal support for an alternative, conflicting bipartition among a set of 323 trees compared to a given bipartition present in the reference topology, which is indicative of 324 high conflict. Therefore, we investigated incongruence in all internodes in the reference 325 phylogeny (Figure 1) that exhibited IC scores lower than 0.1. To calculate IC values for each 326 bipartition for the reference phylogeny, we created a file with all 1,668 complete and partial 327 single gene trees. The resulting file of gene trees, specified with the "-z" parameter in RAXML, 328 were used to calculate IC values using the "-f i" argument. The topology was specified with the 329 "-t" parameter. Lastly, we used the Lossless corrected IC scoring scheme, which corrects for variation in taxon number across single gene trees⁴⁴. We also used these IC values to inform 330 331 which data type (NT or AA) provided the strongest signal for the given set of taxa and 332 sequences. We observed that NTs consistently exhibited higher IC scores than AAs (hence our 333 decision to use the topology inferred from the full NT data matrix using a gene-partitioned 334 scheme - shown in Figure 1 - as the 'reference' topology in all downstream analyses).

335

336 Examining gene-wise log-likelihood scores for incongruent internodes

To determine the per gene distribution of phylogenetic signal supporting a bipartition in thereference phylogeny or a conflicting bipartition, we calculated gene-wise log-likelihood scores

339 (GLS)⁴² using the NT data matrix. We chose to calculate GLS using the NT data matrix because

340 distributions of IC values from phylogenies inferred using NTs had consistently higher IC values

341 across schemes and data matrices (Figure S6). To do so, we used functions available in IQ-

342 TREE. More specifically, we inputted a phylogeny with the reference or alternative topology

343 using the "-te" parameter and informed IQ-TREE of gene boundaries, their corresponding

344 models, and optimal rate heterogeneity parameters in the full 1,668-gene data matrix using the "-

345 spp" parameter. Lastly, we specified that partition log-likelihoods be outputted using the "-wpl"

346 parameter. To determine if a gene provided greater support for the reference or alternative

347 bipartition, we calculated the difference in GLS (Δ GLS) using the following formula:

348

$$\Delta GLS_i = \ln L(G_i)_{ref} - \ln L(G_i)_{alt}$$

where $ln L(G_i)_{ref}$ and $ln L(G_i)_{alt}$ represent the log-likelihood values for the reference and alternative topologies for gene G_i . Thus, values greater than 0 reflect genes in favor of the reference bipartition, values lower than 0 reflect genes in favor of the alternative bipartition, and values of 0 reflect equal support between the reference and alternative bipartitions.

353

354 Calculating gene support frequencies for reference and conflicting bipartitions

We next examined support for bipartitions in the reference topology as well as for their most prevalent conflicting bipartitions by calculating their gene support frequencies (GSF). GSF refers to the fraction of single gene trees that recover a particular bipartition. Currently, RAXML can

358 only calculate GSF for trees with full taxon representation. Since our dataset contained partial 359 gene trees, we conducted customs tests for determining GSF. To calculate GSF for NT (GSF_{NT}) 360 and AA (GSF_{AA}) single gene trees, we extracted subtrees for the taxa of interest in individual 361 single gene trees and counted the occurrence of various topologies. For example, consider there 362 are three taxa represented as A, B, and C, the reference rooted topology is "((A,B),C);" and the 363 alternative rooted topology is "((A,C),B);". We counted how many single gene trees supported 364 "(A,B)," or "(A, C),". For reference and alternative topologies involving more than three taxa or 365 sections, we conducted similar tests. For example, if the reference rooted topology is 366 "(((A,B),C),D);" and the alternative rooted topology is "((A,B),(C,D));", we counted how many 367 single gene phylogenies supported "((A,B),C)," as sister to D and how many single gene 368 phylogenies supported "(A,B)," and "(C,D)," as pairs of sister clades. For conflicting bipartitions 369 at shallow depths in the phylogeny (i.e., among closely related species), we required all taxa to 370 be present in a single gene tree; for conflicting bipartitions near the base of the phylogeny (i.e., 371 typically involving multiple sections), we required at least one species to be present from each 372 section of interest (with the exception of *Exilicaulis* because this section is not monophyletic). 373 Scripts to determine GSF were written using functions provided in NEWICK UTILITIES, version 1.6⁹⁵. 374

375

376 **Estimating divergence times**

To estimate the divergence times for the phylogeny of the Aspergillaceae, we analyzed our NT data matrix used the Bayesian method implemented in MCMCTREE from the PAML package, version 4.9d⁹⁶. To do so, we conducted four analyses: we (i) identified genes evolving in a "clock-like" manner from the full data matrix, (ii) estimated the substitution rate across these

genes, (iii) estimated the gradient and Hessian⁹⁷ at the maximum likelihood estimates of branch
lengths, and (iv) estimated divergence times by Markov chain Monte Carlo (MCMC) analysis.

384 (i) Identifying "clock-like" genes

385 Currently, large phylogenomic data matrices that contain hundreds to thousands of genes and

386 many dozens of taxa are intractable for Bayesian inference of divergence times; thus, we

387 identified and used only those genes that appear to have evolved in a "clock-like" manner in the

388 inference of divergence times. To identify genes evolving in a "clock-like" manner, we

389 calculated the degree of violation of a molecular clock (DVMC)⁹⁸ for single gene trees. DVMC

is the standard deviation of root to tip distances in a phylogeny and is calculated using the

391 following formula:

392
$$DVMC = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (t_i - \bar{t})^2}$$

where t_i represents the distance between the root and species *i* across *n* species. Using this method, genes with low DVMC values evolve in a "clock-like" manner compared to those with higher values. We took the top scoring 834 (50%) genes and bootstrap subsampled 250 genes without replacement. We decided to use 250 genes because a previous study with a similar number of taxa used a similar number of genes⁹⁸.

398

399 (ii) Estimating substitution rate

400 To estimate the substitution rate across the 250 genes, we used BASEML from the PAML package,

401 version 4.9d⁹⁶. We estimated substitution rate using a "GTR+G" model of substitutions (model =

402 7) and a strict clock model (clock = 1). Additionally, we point calibrated the root of the tree to 96

403 million years ago (mya) according to TIMETREE⁹⁹, which is based on previous estimations ¹⁰⁰:
404 50.0 mya; ¹⁰¹: 96.1 mya; ¹⁰²: 146.1 mya. We found the estimated per site substitution rate per
405 time unit was 0.04.

406

407 (iii) Estimation of the gradient and Hessian

408 To save computing time, the likelihood of the alignment was approximated using a gradient and

409 Hessian matrix. The gradient and Hessian refer to the first and second derivatives of the log-

410 likelihood function at the maximum likelihood estimates of branch lengths⁹⁷, and collectively

411 describe the curvature of the log-likelihood surface. Estimating gradient and Hessian requires an

412 input tree with specified time constraints. For time constraints, we used the Aspergillus flavus –

413 Aspergillus oryzae split (3.68-3.99 mya^{102,103}), the Aspergillus fumigatus – Aspergillus clavatus

414 split (35-59 mya^{102,103}), the origin of the genus *Aspergillus* (43-85 mya^{102,104-107}), and the origin

415 of Aspergillaceae (50-146 mya¹⁰⁰⁻¹⁰²) as obtained from TIMETREE⁹⁹.

416

417 (iv) Estimating divergence times using MCMC analysis

418 To estimate divergence times, we used the resulting gradient and Hessian results from the previous step for use in MCMC analysis using MCMCTREE⁹⁶. To do so, a gamma distribution 419 420 prior shape and scale must be specified. The gamma distribution shape and scale is determined from the substitution rate determined in step ii where shape is $a=(s/s)^2$ and scale is $b=s/s^2$ and s 421 422 is the substitution rate. Therefore, a=1 and b=25 and the "rgene" gamma" parameter was set to "1 25." We also set the "sigma2 gamma" parameter to "1 4.5." To minimize the effect of initial 423 424 values on the posterior inference, we discarded the first 100,000 results. Thereafter, we sampled 425 every 500 iterations until 10,000 samples were gathered. Altogether, we ran 5.1 million iterations

426	$(100,000 + 500 \times 10,000)$, which is 510 times greater than the recommended minimum for
427	MCMC analysis ¹⁰⁸ . Lastly, we set the "finetune" parameter to 1.

428

429 To determine the stability of inferred divergence time estimates, we constructed two additional

430 matrices of 250 genes, repeated the analyses in steps ii-iv, and compared results. The two

- 431 additional data matrices were constructed by independently bootstrap subsampling 250 genes
- 432 without replacement from the 834 genes with the best DVMC values. We subsequently repeated
- 433 steps ii-iv and conducted correlation analyses between the three sets of 250 genes to determine
- 434 the stability of inferred divergence times.
- 435

436 Statistical analysis and figure making

437 All statistical analyses were conducted in R, version 3.3.2⁹¹. Spearman rank correlation

438 analyses¹⁰⁹ were conducted using the "rcorr" function in the package HMISC, version $4.1-1^{110}$.

439 Stacked barplots, barplots, histograms, scatterplots, and boxplots were made using GGPLOT2,

440 version 2.2.1¹¹¹. Intersection plots (also known as UpSet plots), were made using UPSETR,

441 version 1.3.3¹¹². The topological similarity heatmap and hierarchical clustering was done using

442 PHEATMAP, version 1.0.8¹¹³. Phylogenetic trees were visualized using FIGTREE, version 1.4.3¹¹⁴.

- 443 The phylogenetic tree with the geological time scale was visualized using STRAP, version 1.4^{115} .
- 444 Artistic features of figures (e.g., font size, font style, etc.) were minimally edited using the
- 445 graphic design software Affinity Designer (https://affinity.serif.com/en-us/).

446 **Results**

447 The examined genomes have nearly complete gene sets

- 448 Assessment of individual gene set completeness showed that most of the 93 genomes (81 in the
- ingroup and 12 in the outgroup) used in our study contain nearly complete gene sets and that all
- 450 93 genomes are appropriate for phylogenomic analyses. Specifically, the average percentage of
- 451 BUSCO single-copy genes from the Pezizomycotina database⁵⁵ present was $96.2 \pm 2.6\%$
- 452 (minimum: 81.1%; maximum: 98.9%; Figure S2). Across the 93 genomes, only 3 (3.2%)
- 453 genomes had < 90% of the BUSCO genes present in single-copy (*Penicillium carneum*: 88.6%;
- 454 *Penicillium verrucosum*: 86.1%; and *Histoplasma capsulatum*: 81.1%).

455

456 The generated data matrices exhibit very high taxon occupancy

457 The NT and AA alignments of the 1,668-gene data matrix were comprised of 3,163,258 and 458 1,054,025 sites, respectively. The data matrix exhibited very high taxon occupancy (average 459 gene taxon occupancy: $97.2 \pm 0.1\%$; minimum: 52.7%; maximum: 100%; Figure S7a, b; File 460 S2). 417 genes had 100% taxon-occupancy, 1,176 genes had taxon-occupancy in the 90% to 461 99.9% range, and only 75 genes had taxon occupancy lower than 90%. Assessment of the 1,668 462 genes for five criteria associated with strong phylogenetic signal (gene-wise alignment length, 463 average bootstrap value, completeness, treeness / RCV, and the number of variable sites) 464 facilitated the construction of five subsampled matrices derived from 50% of the top scoring 465 genes (Figure S7; File S2).

466

467 Examination of the gene content differences between the 5 NT subsampled data matrices as well468 as between the 5 AA data matrices revealed that they are composed of variable sets of genes

469 (Figure S8). For example, the largest intersection among NT data matrices comprised of 207

- 470 genes that were shared between all NT matrices except the completeness-based one; similarly,
- 471 the largest intersection among AA data matrices was 228 genes and was shared between all AA
- 472 matrices except the completeness-based one (Figure S8a, b). Examination of the number of gene
- 473 overlap between the NT and AA data matrices for each criterion (Figure S8c) showed that three
- 474 criteria yielded identical or nearly identical NT and AA gene sets. These were completeness (834

475 / 834; 100% shared genes; $r_s = 1.00$, p < 0.01; Figure S7c), alignment length (829 / 834; 99.4%)

476 shared genes; $r_s = 1.00$, p < 0.01; Figure S7f), and the number of variable sites (798 / 834; 95.7%)

477 shared genes; $r_s = 0.99$, p < 0.01; Figure S7i). The other two criteria showed greater differences

- 478 between NT and AA data matrices (average bootstrap value: 667 / 834; 80.0% shared genes; $r_s =$
- 479 0.78, p < 0.01; Figure S7l; treeness / RCV: 644 / 834; 77.2% shared genes; $r_s = 0.72$, p < 0.01;
- 480 Figure S7o).
- 481

482 A genome-scale phylogeny for the family Aspergillaceae

NT and AA phylogenomic analyses of the full data matrix and the five subsampled data matrices under three analytical schemes recovered a broadly consistent set of relationships (Figure 1, 2, 3, 4). Across all 36 species-level phylogenies, we observed high levels of topological similarity (average topological similarity: $97.2 \pm 2.5\%$; minimum: 92.2%; maximum: 100%) (Figure 2), with both major genera (*Aspergillus* and *Penicillium*) as well as all sections, with the exception of *Exilicaulis*, in *Aspergillus* and *Penicillium*^{50,116} recovered as monophyletic (Figures 1, 3, and 4). Additionally, all but one internodes exhibited absolute UFBoot scores⁸⁴; the sole exception

490 was internode 33 (I33), which received 95 UFBoot support (Figure 1 and S9).

491

492	Surprisingly, one taxon previously reported to be part of Aspergillaceae, Basipetospora
493	chlamydospora, was consistently placed among outgroup species (Figure 1) and may represent a
494	misidentified isolate. A similarly surprising placement was observed for Aspergillus
495	ochraceoroseus IBT 24754 ³³ , which our phylogenies consistently placed in section Nigri (Figure
496	1) rather than, as expected based on previous work, in section Ochraceorosei ¹¹⁷ . To explore this
497	placement further, we reconstructed a phylogeny of closely related Aspergillus species from
498	sections Flavi, Ochraceorosei, Usti, Versicolores, Nidulantes, and Nigri and included another A.
499	ochraceoroseus isolate, strain SRRC1432 ¹¹⁸ using the same set of 1,668 BUSCO genes as well
500	as a larger set of 3,150 BUSCO genes. Phylogenomic analysis of these two data matrices
501	recovered A. ochraceoroseus SRRC1432 as sister to A. rambellii in section Ochraceorosei,
502	consistent with the original description of section Ochraceorosei ¹¹⁹ . In contrast, A.
503	ochraceoroseus IBT 24754 remained placed within Nigri (Figure S10a and b). Hypothesizing
504	that A. ochraceoroseus IBT 24754 may represent a misidentified isolate, we examined its
505	genome size and number of genes in relation to those of A. ochraceoroseus SRRC1432 and A.
506	rambellii and found them to be very different (Figure S10c). Specifically, A. ochraceoroseus IBT
507	24754 has 11,939 genes and a genome size of 35.4 Mbp while A. ochraceoroseus SRRC1432
508	and A. rambellii have gene counts of 7,829 and 7,761 and genome sizes of 24.3 and 26.4 Mbp.
509	Together, these results suggest that A. ochraceoroseus IBT 24754 is a misidentified Aspergillus
510	species belonging to section Nigri; to avoid further confusion, we henceforth refer to this strain
511	as A. spp. IBT 24574 (Figure S10d).
512	

513 Examination of the Aspergillaceae phylogeny reveals 12 incongruent bipartitions

514 Examination of all 36 species-level phylogenies revealed the existence of 8 (8 / 78; 10.3%)

515 incongruent bipartitions. Complementary examination of IC, a bipartition-based measure of

516 incongruence, revealed an additional 4 / 78 (5.1%) bipartitions that displayed very high levels of

517 incongruence at the gene level, raising the total number of incongruent bipartitions to 12 (12 /

518 78; 15.4%).

519

520 Examination of the eight conflicting bipartitions stemming from the comparison of the 36 521 phylogenies showed that they were very often associated with data type (NT or AA) and scheme 522 employed (concatenation or coalescence). For example, the first instance of incongruence 523 concerns the identity of the sister species to Penicillium biforme (I60; Figure 1 and 3a); this 524 species is *P. camemberti* in the reference phylogeny but analyses of the full and two subsampled 525 AA data matrices with coalescence recover instead *Penicillium fuscoglaucum*. The data type and 526 analytical scheme employed also appear to underlie the second and third instances of 527 incongruence, which concern the polyphyly of section *Exilicaulis* (I74 and I78; Figures 1 and 528 3b), the fourth and fifth instances, which concern relationships among Aspergillus sections (I24 529 and I35; Figures 1 and 3c), as well as the sixth instance, which concerns relationships among the 530 sections Digitata, Chrysogena, and Roquefortorum (I63; Figure 1 and 3d). The seventh instance 531 is also associated with data type, but not with the scheme employed; while the reference as well 532 as most subsampled NT matrices support the Aspergillus persii and Aspergillus sclerotiorum 533 clade as sister to Aspergillus westerdijkiae (I33; Figure 1 and 3e), most AA data matrices recover 534 a conflicting bipartition where A. steynii is the sister group of A. westerdijkiae. The final instance 535 of incongruence was the least well supported, as 35 / 36 (97.2%) phylogenies supported

Aspergillus kawachii as the sister group to Aspergillus awamori (I15, Figure 1 and 3f), but
analysis of one AA subsampled data matrix with coalescence instead recovered Aspergillus *luchuensis* as the sister group.

539

540 For each of these bipartitions (Figure 3), we examined clustering patterns using multiple 541 correspondence analysis of matrix features (i.e., sequence type and subsampling method) and 542 analysis scheme among trees that support the reference and alternative topologies (Figure S11). 543 Distinct clustering patterns were observed for I74, I78, and I33 (Figure 3 and S11). For I74 and 544 178, there are three alternative, conflicting topologies, with the first two clustering separately 545 from the third (Figure 3b and S11b). For I33, phylogenies that support the reference and 546 alternative topologies formed distinct clusters (Figure 3e). Examination of the contribution of 547 variables along the second dimension, which is the one that differentiated variables that 548 supported each topology, revealed that the distinct clustering patterns were driven by sequence 549 type (Figure S11g and h).

550

551 Examination of IC values revealed four additional bipartitions with strong signatures for 552 incongruence at the gene level, defined as IC score lower than 0.10. The first instance concerns 553 the sister taxon to the Aspergillus and Penicillium clade. Although all 36 phylogenies recover a 554 clade comprised of *Xeromyces bisporus* and *Monascus ruber* as the sister group, the IC score for 555 this bipartition is 0.00 (I3; Figure 4a); the most prevalent, conflicting bipartition supports 556 *Penicilliopsis zonata* as sister to *Aspergillus* and *Penicillium* (Figure 4a). Similarly, although all 557 36 phylogenies recover *Penicillium* as sister to *Aspergillus*, the IC score for this bipartition is 558 also 0.00 (I4; Figure 4b); the most prevalent, conflicting bipartition supports X. bisporus and M.

559	ruber as the sister clade to Aspergillus (Figure 4b). In the third instance, all 36 phylogenies
560	support Aspergillus novofumigatus and Aspergillus lentulus as sister species, but the IC score of
561	this bipartition is 0.01 (I43; Figure 4c); the most prevalent, conflicting bipartition recovers A.
562	lentulus as the sister species to a clade comprised of Aspergillus fumigatus and Aspergillus
563	fischeri (Figure 4c). Finally, all 36 phylogenies supported a clade of Penicillium solitum,
564	Penicillium polonicum, and Penicillium freii as sister to a clade of Penicillium nordicum and
565	Penicillium verrucosum, but the IC score for this bipartition is 0.01 (I55; Figure 4d); the most
566	prevalent, conflicting bipartition supports the clade of P. solitum, P. polonicum, and P. freii as
567	sister to a clade of P. camemberti, P. biforme and P. fuscoglaucum (Figure 4d).
568	
569	To examine the underlying individual gene support to the resolution of these 12 bipartitions, we
570	examined the phylogenetic signal contributed by each individual gene in the full NT data matrix.
571	In all 12 bipartitions, we found that inferences were robust to single gene outliers with strong
572	phylogenetic signal (Figure S12; File S4).

573

574 **Incongruence in the Aspergillaceae phylogeny**

Examination of the 12 incongruent bipartitions with respect to their placement on the phylogeny (shallow, i.e., near the tips of the phylogeny or deeper, i.e., away from the tips and toward the base of the phylogeny) and the amount of conflict (quantified using IC and GSF) allowed us to group them into three categories: (i) shallow bipartitions (I15 and I60) with low levels of incongruence, (ii) shallow bipartitions (I33, I43, and I55) with high levels of incongruence, and (iii) deeper bipartitions (I3, I4, I24, I35, I63, I74, and I78) with varying levels of incongruence and typically associated with single taxon long branches.

5	0	2
J	0	Ζ

- 583 (i) Shallow bipartitions with low levels of incongruence
- 584 The two bipartitions that fell into this category, I60 (Figure 3a) and I15 (Figure 3f), exhibited
- 585 low levels of incongruence among closely related taxa. For I60, the reference bipartition was
- observed in 33 / 36 phylogenies, had an IC score of 0.22, and GSF_{NT} and GSF_{AA} scores of 0.70
- and 0.21, respectively. Similarly, the reference bipartition for I15 was observed in 35 / 36
- 588 phylogenies, had an IC score of 0.39, and GSF_{NT} and GSF_{AA} scores of 0.84 and 0.47,
- 589 respectively. Notably, the GSF_{NT} scores were substantially higher for the reference bipartitions in
- 590 both of these cases.
- 591
- 592 (ii) Shallow bipartitions with high levels of incongruence
- 593 The three shallow bipartitions, I33 (Figure 3e), I43 (Figure 4c), and I55 (Figure 4d), in this
- 594 category exhibited high levels of incongruence among closely related taxa. For I33, the reference
- 595 bipartition was observed in 16 / 36 (44.4%), had an IC score of 0.00, and GSF_{NT} and GSF_{AA}
- scores of 0.38 and 0.27, respectively. The reference bipartition for I43 was observed in all 36
- 597 phylogenies, had an IC score of 0.01 and GSF_{NT} and GSF_{AA} scores of 0.39 and 0.22,
- respectively. Similarly, the reference bipartition I55 was observed in all 36 phylogenies, had an
- 599 IC score of 0.01, and GSF_{NT} and GSF_{AA} scores of 0.51 and 0.31, respectively. Notably, in all
- 600 three cases, substantial fractions of genes supported both the reference and the conflicting
- 601 bipartitions, with both the GSF_{NT} and GSF_{AA} scores of each pair of bipartitions being almost
- 602 always higher than 0.2.
- 603
- 604 (iii) Deeper bipartitions often associated with single taxon long branches

605	The seven bipartitions in this category were I74 and I78 (Figure 3b), I24 and I35 (Figure 3c), I63
606	(Figure 3d), I3 (Figure 4a), and I4 (Figure 4b). All of them are located deeper in the tree and
607	most involve single taxa with long terminal branches (Figure 1). The reference bipartitions for
608	internodes I74 and I78, which concern relationships among the sections Lanata-divaricata,
609	<i>Exilicaulis</i> and <i>Citrina</i> , were observed in 26 / 36 (72.2%) phylogenies; the remaining $10 / 36$
610	(27.8%) phylogenies recovered three alternative, conflicting bipartitions. Both reference
611	bipartitions had IC scores of 0.01, and GSF _{NT} and GSF _{AA} scores of 0.11 and 0.07, respectively.
612	The reference bipartitions for internodes I24 and I35, which concern the placement of
613	Aspergillus terreus, the single taxon representative of section Terrei, were observed in 27 / 36
614	(75.0%) phylogenies, had IC scores of 0.01 and 0.02, and GSF_{NT} and GSF_{AA} scores of 0.17 and
615	0.09, respectively. The reference bipartition I63, which involved the placement of the
616	Penicillium digitatum, the sole representative of section Digitata, was observed in 28 / 36
617	(77.8%), had an IC score of 0.07, and GSF_{NT} and GSF_{AA} scores of 0.41 and 0.28, respectively.
618	Finally, the reference bipartitions I3 and I4 (Figure 4), which concern the identity of the sister
619	taxon of Aspergillus and Penicillium (I3) and the identity of the sister taxon of Aspergillus (I4),
620	were not observed among the 36 phylogenies but both had IC values of 0.00. For I3, GSF_{NT} and
621	GSF_{AA} scores were 0.12 and 0.15, respectively. For I4, GSF_{NT} and GSF_{AA} scores were 0.24 and
622	0.28, respectively.

623

624 A geological timeline for the evolutionary diversification of the Aspergillaceae

625 family

626 To estimate the evolutionary diversification among *Aspergillaceae*, we subsampled the 1,668-

627 gene matrix for high-quality genes with "clock-like" rates of evolution by examining DVMC ⁹⁸

628	values among single gene trees. Examination of the DVMC values facilitated the identification
629	of a tractable set of high-quality genes for relaxed molecular clock analyses (Figure S13). We
630	found that Aspergillaceae originated 125.1 (95% CI: 146.7 - 102.1) mya during the Cretaceous
631	period (Figure 5). We found that the common ancestor of Aspergillus and Penicillium split from
632	the X. bisporus and M. ruber clade shortly thereafter, approximately 114.3 (95% CI: 135.5 -
633	96.5) mya. We also found that the genera Aspergillus and Penicillium split 102.4 (95% CI: 122.3
634	- 88.2) mya, with the last common ancestor of Aspergillus originating approximately 84.3 mya
635	(95% CI: 90.9 - 77.6) and the last common ancestor of <i>Penicillium</i> originating approximately
636	77.4 mya (95% CI: 94.0 - 61.0).
637	
638	Our analysis also provides estimates of the origin of various iconic sections within Aspergillus
639	and Penicillium. Among Aspergillus sections, section Nigri, which includes the industrial
640	workhorse A. niger, originated 51.6 (95% CI: 63.4 - 38.1) mya. Section Flavi, which includes the
641	food fermenters A. oryzae and A. sojae and the plant pathogen A. flavus, originated 32.6 (95%
642	CI: 45.5 - 22.4) mya. Additionally, section Fumigati, which includes the opportunistic human
643	pathogen A. fumigatus, originated 17.4 (95% CI: 24.7 - 11.9) mya. Among Penicillium sections,
644	section Fasiculata, which contains Camembert and Brie cheese producer P. camemberti and the
645	ochratoxin A producer, P. verrucosum, originated 7.1 (95% CI: 10.9 - 4.1) mya. Section
646	Chrysogena, which includes the antibiotic penicillin producing species P. chrysogenum,
647	originated 6.4 (95% CI: 11.5 - 3.2) mya. Additionally, section Citrina, which contains P.
648	citrinum, which the first statin was isolated from and is commonly associated with moldy citrus
649	fruits (Endo et al. 1976), originated 32.4 (95% CI: 46.1 - 20.8) mya.
650	

651 **Discussion**

652 Our analyses provide a robust evaluation of the evolutionary relationships and diversification 653 among Aspergillaceae, a family of biotechnologically and medically significant fungi. We 654 scrutinized our proposed reference phylogeny (Figure 1) against 35 other phylogenies recovered 655 using all possible combinations of six multi-gene data matrices (full or subsamples thereof), 656 three maximum likelihood schemes, and two sequence types and complemented this analysis 657 with bi-partitioned based measures of support (Figures 1 and 2). Through these analyses, we 658 found that 12/78 (15.4%) bipartitions were incongruent (Figure 3 and 4) and explored the 659 characteristics as well as sources of these instances of incongruence. Finally, we placed the 660 evolution and diversification of Aspergillaceae in the context of geological time. 661 662 Comparison of our 81-taxon, 1,668-gene phylogeny to a previous one based on a maximum likelihood analysis of 9 loci for 204 Aspergillaceae species¹¹⁶, suggests that our analyses 663 664 identified and strongly supported several new relationships and resolved previously low 665 supported bipartitions (Figure 1, Figure S14). The robust resolution of our phylogeny is likely 666 due to the very large size of our data matrix, both in terms of genes as well as in terms of 667 sequence. For example, the placement of *Aspergillus* section *Nigri* has been unstable in previous phylogenomic analyses (Figure S1) 31,33,34 , but our denser sampling of taxa in this section as well 668 669 as inclusion of representative taxa from sections Nidulantes, Versicolores, Usti, and 670 Ochraceorosei now provides strong support for the sister relationship of the Aspergillus section 671 Nigri to sections Nidulantes, Versicolores, Usti, and Ochraceorosei (Figure 1). 672

673 However, our analysis also identified several relationships that exhibit high levels of 674 incongruence (Figures 3 and 4). In general, gene tree incongruence can stem from biological or analytical factors^{30,42}. Biological processes such as incomplete lineage-sorting (ILS)¹²¹, 675 hybridization¹²², gene duplication and subsequent loss¹²³, horizontal gene transfer¹²⁴, and natural 676 677 selection^{125,126}, can cause the histories of genes to differ from one another and from the species 678 phylogeny. Importantly, although the expected patterns of incongruence will be different for 679 each factor and depend on a number of parameters, the observed patterns of conflict in each of the 12 cases of incongruence in the Aspergillaceae phylogeny can yield insights and allow the 680 681 formation of hypotheses about the potential drivers in each case. For example, ILS often results 682 in relatively low levels of incongruence; for instance, examination of the human, chimp, and 683 gorilla genomes has showed that 20-25% of the gene histories differ from the species phylogeny^{127,128}. In contrast, recent hybridization is expected to typically produce much higher 684 685 levels of incongruence due to rampant sequence similarity among large amounts of genomic 686 content; for instance, examination of *Heliconius* butterfly genomes revealed incongruence levels 687 higher than $40\%^{129}$.

688

Additionally, analytical factors such as model choice¹³⁰ and taxon sampling^{131,132} can lead to erroneous inference of gene histories. Perhaps the most well-known instance of incongruence stemming from analytical factors is what is known as "long branch attraction", namely the situation where highly divergent taxa, i.e., the ones with the longest branches in the phylogeny, will often artifactually group with other long branches¹³³.

694

695 Examination of the patterns of incongruence in the Aspergillaceae phylogeny allows us to not 696 only group the 12 incongruent internodes with respect to their patterns of conflict but also to 697 postulate putative drivers of the observed incongruence. For example, both 115 and 160 are 698 shallow internodes exhibiting low levels of incongruence, suggesting that one likely driver of the 699 observed incongruence is ILS. In contrast, the shallow internodes I33, I43, and I55 exhibit much 700 higher levels of incongruence that are most likely to be the end result of processes, such as 701 hybridization or repeated introgression. Finally, the remaining seven incongruent internodes (I3, 702 14, 124, 135, 163, 174, and 178) exhibit varying levels of incongruence and are typically associated 703 with single taxon long branches (Figures 1, 3, and 4), implicating taxon sampling as a likely 704 driver of the observed incongruence. Given that inclusion of additional taxa robustly resolved the 705 previously ambiguous placement of the long-branched Aspergillus section Nigri (see discussion 706 above), we predict that additional sampling of taxa that break up the long branches associated 707 with these seven internodes will lead to their robust resolution.

708

Finally, our relaxed molecular clock analysis of the Aspergillaceae phylogeny provides a robust but also comprehensive time-scale for the evolution of Aspergillaceae and its two large genera, *Aspergillus* and *Penicillium* (Figure 5), filling a gap in the literature. Previous molecular clock studies provided estimates for only four internodes, mostly within the genus *Aspergillus*^{99–107} and yielded much greater time intervals. For example, the previous estimate for the origin of Aspergillaceae spanned nearly 100 mya (50-146 mya^{100–102}) while our dataset and analysis provided a much narrower range of 44.5 mya (mean: 125.1; 95% CI: 146.7 - 102.1).

717 Conclusion

718 Fungi from Aspergillaceae have diverse ecologies and play significant roles in biotechnology 719 and medicine. Although most of the 81 genomes from Aspergillaceae are skewed towards two 720 iconic genera, *Aspergillus* and *Penicillium*, and do not fully reflect the diversity of the family, 721 they do provide a unique opportunity to examine the evolutionary history of these important 722 fungi using a phylogenomic approach. Our scrutiny of the Aspergillaceae phylogeny, from the 723 Cretaceous to the present, provides strong support for most relationships within the family as 724 well as identifies a few that deserve further examination. Our results suggest that the observed 725 incongruence is likely associated with diverse processes such as incomplete lineage sorting, 726 hybridization and introgression, as well as with analytical issues associated with poor taxon 727 sampling. Our elucidation of the tempo and pattern of the evolutionary history of Aspergillaceae 728 provides a robust phylogenetic and temporal framework for investigation the evolution of pathogenesis, secondary metabolism, and ecology of this diverse and important fungal family. 729

730 Data availability

- All data matrices, species-level and single-gene phylogenies will be available through the
- figshare repository upon acceptance for publication. The genome sequence and raw reads of
- 733 Aspergillus delacroxii have been uploaded to GenBank as BioProject PRJNA481010.

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742 Main Figure Legends

743 Figure 1. A robust genome-scale phylogeny for the fungal family Aspergillaceae.

744 Different genera are depicted using different colored boxes; Aspergillus is shown in red,

745 *Penicillium* in blue, *Xeromyces* in green, *Monascus* in purple, and *Penicilliopsis* in orange.

746 Different sections within Aspergillus and Penicillium are depicted with alternating dark grey and

747 grey bars. Internode certainty values are shown below each internode and bootstrap values are

shown above each internode (only bootstrap values lower than 100 percent supported are

shown). Internode certainty values were calculated using the 1,668 maximum likelihood single

gene trees. 5,000 ultrafast bootstrap replicates were used to determine internode support.

751 Internodes were considered unresolved if they were not present in one or more of the other 35

752 phylogenies represented in Figure 2 – the branches of these unresolved internodes are drawn in

red. The inset depicts the phylogeny with branch lengths corresponding to estimated nucleotide

substitutions per site. Colored circles next to species names indicate the lifestyle or utility of the

755 species (i.e., animal pathogen, dark orange; plant pathogen, purple; food fermenter, green; post-

harvest food contaminant, pink; industrial workhorse, grey; genetic model, black; other, white).

757 Exemplary secondary metabolites produced by different Aspergillaceae species are depicted to

the right of the colored circles.

759

Figure 2. Topological similarity between the 36 phylogenies constructed using 6 different data matrices, 2 different sequence types, and 3 analytical schemes.

(a) A heatmap depiction of topological similarity between the 36 phylogenies constructed in this

study. The 36 phylogenies were inferred from analyses of 2 different sequence types (i.e.,

764 protein: depicted in black; nucleotide: depicted in white), 3 different analytical schemes (i.e.,

765	partitioned: depicted in black; non-partitioned: depicted in grey; coalescence: depicted in white)
766	and 6 different matrices (full data matrix: "BUSCO1668", and 5 subsampled ones, all starting
767	with "T834"; depending on the subsampling strategy, they are identified as "T834 Alignment
768	lengths", "T834 Average bootstrap value", "T834 Completeness", "T834 Treeness / RCV", and
769	T834 Variable sites"). (b) Hierarchical clustering based off of topological similarity values
770	among the 36 phylogenies.

771

772 Figure 3. The eight internodes not recovered in all 36 phylogenies.

773 Internode numbers refer to internodes that have at least one conflicting topology among the 36 774 phylogenetic trees inferred from the full and five subsampled data matrices across three different 775 schemes and two data types. The internode recovered from the analysis of the 1,668-gene 776 nucleotide matrix (Figure 1) is shown on the left and the conflicting internode(s) on the right. 777 Next to each of the internodes, the nucleotide (nt) and amino acid (aa) gene support frequency 778 (GSF) values are shown. On the far right, the sequence type, scheme, and data matrix 779 characteristics of the phylogenies that supports the conflicting internodes are shown. Nt and aa 780 sequence types are represented using black and white squares, respectively; partitioned 781 concatenation, non-partitioned concatenation, and coalescence analytical schemes are depicted as 782 black, grey, or white circles, respectively; and the matrix subset is written next to the symbols. 783

Figure 4. The four internodes recovered in all 36 phylogenies but that exhibit very low internode certainty values.

Four bipartitions were recovered by all 36 phylogenies but had internode certainty values below
0.10. The internode recovered from the analysis of all 36 phylogenies, including of the 1,668-

788	gene nucleotide matrix	(Figure 1).	is shown o	on the	left and	the most	prevalent.	conflicting
100	Selle maereoriae matrix	1 15010 1	- 19	10 0110 011 0		ivit ullu	the most	preverence	commetting

- internode on the right. Next to each of the internodes, the nucleotide (nt) and amino acid (aa)
- 790 gene support frequency (GSF) values are shown.
- 791

792 Figure 5. A molecular timetree for the family Aspergillaceae.

- 793 Blue boxes around each internode correspond to 95% divergence time confidence intervals for
- each branch of the Aspergillaceae phylogeny. For reference, the geologic time scale is shown
- right below the phylogeny. Different genera are depicted using different colored boxes;
- 796 Aspergillus is shown in red, Penicillium in blue, Xeromyces in green, Monascus in purple, and
- 797 Penicilliopsis in orange. Different sections within Aspergillus and Penicillium are depicted with
- alternating dark grey and grey bars. Dating estimates were calibrated using the following
- constraints: origin of Aspergillaceae (I2; 50-146 million years ago [mya]), origin of Aspergillus
- 800 (I5; 43-85 mya) the A. flavus and A. oryzae split (I30; 3.68-3.99 mya), and the A. fumigatus and
- 801 A. clavatus split (I38; 35-39 mya); all constraints were obtained from TIMETREE⁹⁹.

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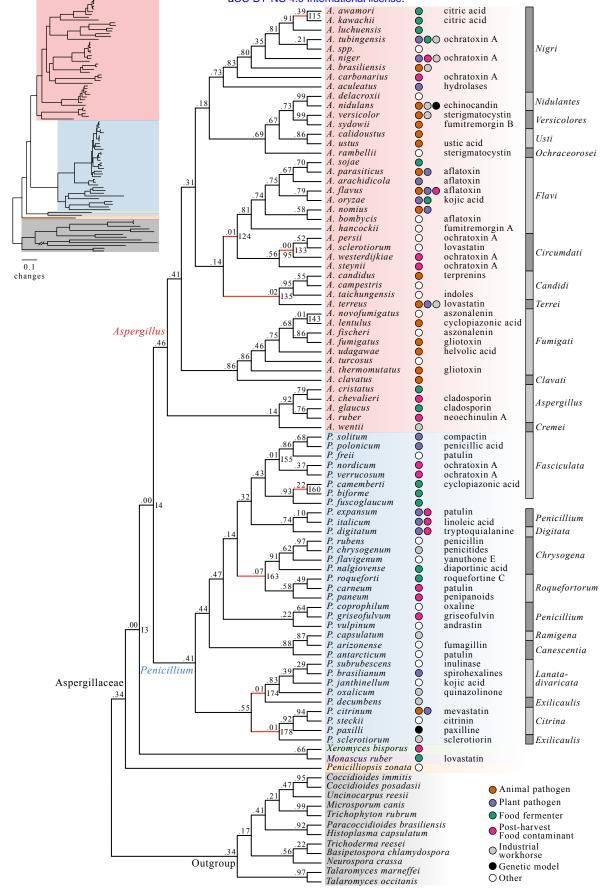
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			aCC-	BY-NC 4.0 International license.			Type Scheme □NT □AA ○Coalescence
	Reference topology	GS NT		Alternative topology		SF AA	Matrices with alt. topology
a		.70	.36	Penicillium fuscoglaucum Penicillium biforme Penicillium camemberti	.21	.51	 BUSCO1668 T834 Comp. T834 T/RCV
b				i Lanata-divaricata Citrina Penicillium decumbens Penicillium sclerotiorum	.08	.08	☐ 0 T834 ABV ☐ 0 T834 T/RCV ☐ 0 T834 VS
1	<u>.01</u> 174 Penicillium decumbens <u>.01</u> 178 Citrina Penicillium sclerotiorum	.11	.07	ii Lanata-divaricata Penicillium decumbens Citrina Penicillium sclerotiorum	.08	.07	☐O T834 Comp.
				iii Citrina Penicillium decumbens Lanata-divaricata Penicillium sclerotiorum	.08	.09	 BUSCO1668 T834 AL T834 ABV T834 Comp. T834 T/RCV T834 VS
c	.01 Flavi Circumdati .02 135 Candidi Terrei	.17	.09	Flavi Circumdati Terrei Candidi	.09	.10	 BUSCO1668 T834 AL T834 Comp. T834 T/RCV T834 VS
d	Digitata Chrysogena Roquefortorum Penicillium Penicillium; P. coprophilum, P. griseofulvum, P. vulpinum	.41	.28	Digitata Roquefortorum Chrysogena Penicillium: P. coprophilum, P. griseofulvum, P. vulpinum	.31	.36	 BUSCO1668 T834 AL T834 ABV T834 Comp. T834 T/RCV T834 VS
e	.00 Aspergillus persii Aspergillus sclerotiorum Aspergillus westerdijkiae Aspergillus steynii	, .38	.27	Aspergillus persii Aspergillus sclerotiorum Aspergillus westerdijkiae Aspergillus steynii	.35	.46	 BUSCO1668 T834 AL T834 ABV T834 Comp. T834 T/RCV T834 VS
f	.39 [115] Aspergillus awamori Aspergillus kawachii Aspergillus luchuensis	.84	.47	Aspergillus awamori Aspergillus luchuensis Aspergillus kawachii	.15	.37	T 834 Comp.

Reference topology	GSF NT AA	Alternative topology		SF AA
a .0013 Asp. and Pen. Xeromyces bisporus Monascus ruber Penicilliopsis zonata	.12 .15	Asp. and Pen. Penicilliopsis zonata Xeromyces bisporus Monascus ruber	.08	.12
b <u>.00</u> <u>I4</u> <u>Aspergillus</u> <u>Xeromyces bisporus</u> <u>Monascus ruber</u> <u>Penicilliopsis zonata</u>	.24 .28	Aspergillus Xeromyces bisporus Monascus ruber Penicillium Penicilliopsis zonata	.20	.14
c Aspergillus novofumigatus Aspergillus lentulus entulus Aspergillus fischeri Aspergillus fumigatus	.39 .22	Aspergillus novofumigatus Aspergillus lentulus Aspergillus fischeri Aspergillus fumigatus	.25	.14
d <u>.01</u> [55] Penicillium sp1 Penicillium sp3 sp1: P. solitum, P. polonicum, P. freii sp2: P. nordicum, P. verucosum sp3: P. camemberti, P. biforme, P. fuscoglaucum	.51 .31	Penicillium sp1 Penicillium sp3 Penicillium sp2 sp1: P. solum, P. pelonicum, P. freii sp2: P. nordicum, P. verucosum sp3: P. camemberti, P. biforme, P. fuscoglaucum	.23	.22

aCC-BY-NC 4.0 International license. A. awamori A. kawachii A. luchuca гť luchuensis tubingensis Æ spp. niger Nigri brasiliensis carbonarius aculeatus delacroxii Nidulantes nidulans versicolor Versicolores sydowii calidoustus Usti ustus rambellii Ochraceorosei sojae parasiticus arachidicola flavus Flavi oryzae nomius *bombycis* hancockii persii sclerotiorum Ð Circumdati westerdijkiae steynii

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